9 Beyond Cognitive Systems Engineering: Assessing User Affect and Belief States to Implement Adaptive Pilot-Vehicle Interaction

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ABSTRACT

We describe an Affect and Belief Adaptive Interface System (ABAIS) designed to compensate for performance biases caused by users' affective states and active beliefs. The ABAIS architecture implements an adaptive methodology consisting of four steps: sensing/inferring user affective state and performance-relevant beliefs; identifying their potential impact on performance; selecting a compensatory strategy; and implementing this strategy in terms of specific Graphic User Interface (GUI) adaptations. ABAIS provides a generic adaptive framework for integrating a variety of user assessment methods (e.g., knowledge-based, self-reports, diagnostic tasks, physiological sensing), and GUI adaptation strategies (e.g., content- and format-based). The ABAIS performance bias prediction is based on empirical findings from emotion research combined with detailed knowledge of the task context. The initial ABAIS prototype was demonstrated in the context of a U.S. Air Force combat task, used a knowledge-based approach to assess the pilot's anxiety level, and adapted to the pilot's anxiety and belief states by modifying selected cockpit instrument displays in response to detected changes in those states. Preliminary results indicate feasibility of the ABAIS approach, raise a number of further research questions, and suggest specific requirements for a successful, operational affect and belief-adaptive interface (e.g., limiting the number, type, and resolution of affective and belief states; using multiple methods and individualized data for user state assessment; implementing "benign" adaptations [e.g., adaptations

should never limit access to existing information]). The focus on affect and belief represents a new area of research in joint cognitive systems. Results of this effort suggest that existing cognitive systems engineering methods, and the resulting designs, may not go far enough if they limit themselves to the exclusive consideration of cognitive and motor factors, and fail to place adequate emphasis on affect and beliefs as critical factors influencing performance.

9.1 INTRODUCTION

The mutual influence of cognitive schemata and contextual constraints is considered the accepted basis for cognitive systems engineering practices (Hollnagel & Woods, 1983; Rasmussen, Pejtersen, & Goodstein, 1994). Less generally accepted is the fact that *affective states* can also dramatically influence human performance and decision making, via effects on attention, perception, situation assessment, and ultimately action selection (LeDoux, 1992; Williams et al., 1997).

Recent research provides increasing evidence that individual differences in general, and affective states in particular, have a major impact on performance (Deckert et al., 1994; Eysenck, 1997; Isen, 1993; LeDoux, 1992; Mineka & Sutton, 1992; Williams et al., 1997). Affective states influence a variety of perceptual, cognitive,, and motor processes by influencing both low-level perceptual, cognitive and motor processes (e.g., attention, memory), and by influencing higher-level processes such as situation assessment, decision making, and judgment. Examples of these influences include:

- Altering the nature of attentional processing (e.g., change focal area, increase/reduce size of focal area, bias attention toward or away from particular stimuli, etc.)
- Helping to activate (or inhibit) particular perceptual and cognitive schemata that enhance (or limit) the perception of processing of specific stimuli
- Promoting (or inhibiting) the selection of particular actions, and influencing the accuracy and speed of selected motor responses.

Similarly, experimental studies indicate that the user's current assessment of the situation, in other words, his/her *belief state*, plays a critical role in the decision making and, ultimately, response selection.

As computer systems requiring user adaptation and associated User Interface (UI) technologies mature and proliferate into critical applications, and increasingly heterogeneous user populations, it becomes particularly important that they recognize and adapt to individual user characteristics. To accommodate these requirements, we suggest that Cognitive Systems Engineering (CSE) methods must therefore enlarge their traditional focus on cognition and context to include the user's individual characteristics. Successful user adaptation requires the understanding of these individual characteristics and their interactions with task and situation variables, including other human and synthetic agents, to create successful designs (see McNeese, Chapter 3 this volume). This is particularly true for the user's dynamic characteristics that involve affective and belief states, since both these factors strongly influence performance. This requirement is necessary for the wide variety of decision support and user interface systems being deployed in the aviation domain (e.g., see Reising, Chapter 1 and Taylor et al., Chapter 8 this volume).

While some progress has been made in user-modeling and adaptive user interfaces (see Section 9.3 below), the majority of existing decision-support and cognitive modeling systems continue to assume normative performance, and fail to adapt to the individual characteristics of particular users, whether those that are relatively stable over time, or those that are susceptible to situation influences. This is particularly true for adaptation with respect of the user's current situation assessment (belief states) state and current emotion (affective states).[1]

This existing lack of detection, assessment, and modeling of belief and affective states on the one hand, and adaptation to these states on the other, in the majority of human-machine systems can lead to nonoptimal behavior at best, and critical errors with disastrous consequences at worst. This is increasingly evidenced by a variety of accidents and incidents attributed to the broad area of "human error" that exist in commercial and military aviation, a variety of industry processes, and, increasingly, in health care (Institute of Medicine, 1999).

To address these influences we must develop user models that take into account the effects of affect and belief on performance, and develop strategies for adapting the machine aiding and user interface to the users' individual, possibly idiosyncratic, affect and belief states. A number of issues arise in developing adaptive user interfaces capable of identifying the user's affective and belief state and compensating for the resulting biases in performance. The primary challenges are:

- Effective assessment of the user's current affective state
- Prediction of its influences on performance, in the current task context
- Identification of strategies that could compensate for the potential performance biases
- Generation of corresponding Graphic User Interfaces (GUIs) and associated computer system adaptations.

To address these challenges we developed an Affect and Belief Adaptive Interface System (ABAIS) adaptive methodology and implemented a prototype ABAIS system. The development of ABAIS and the associated adaptive methodology are analogous to cognitive system engineering practices and may be considered as one example of what McNeese (Chapter 3 this volume) con-

1. We use the term "emotion" and "affective state" interchangeably, referring to transient states, with distinct triggers and individual decay functions, roughly at the level of basic emotions or Category 2 emotions (Panskepp, 1994).

siders as a *knowledge as model as design* approach, wherein knowledge is defined as inclusive of affective and belief states. In many cases, however, this approach goes beyond the scope of narrow implementations of cognitive systems engineering by the very fact of including emotions and beliefs.

The ABAIS prototype implements this methodology in terms of an architecture shown in Figure 9.1. The architecture consists of four modules. *User State Assessment* provides a framework for integrating a variety of methods to identify the user's affective and belief state (e.g., knowledge-based, self-reports, diagnostic tasks, physiological sensing). *Impact Prediction* integrates generic empirical findings with the results of task-specific Cognitive Affective Personality Task Analysis (CAPTA) (Hudlicka, 2000a) to predict the most likely effects of user states on performance. *Strategy Selection* combines the CAPTA results with individual preferences to derive an appropriate compensation strategy. Finally, *GUI Adaptation* implements this strategy by modifying the content and/or format of the user interface (see Figure 9.2).

ABAIS implements an adaptive methodology framework capable of adapting the system interface format and content to the user's affective state and situation-specific beliefs that might influence performance (Hudlicka, 2000b; Hudlicka & Billingsley, 1999, 1998).

The ABAIS prototype was developed and demonstrated in the context of an Air Force combat task simulation. ABAIS assessed the pilot's anxiety and belief states via a knowledge-based approach, using information from a variety of sources (e.g., task characteristics, pilot personality, etc.), predicted the effects of user state on performance, and suggested and implemented specific GUI adaptation strategies based on the pilot's information presentation preferences (e.g., modified icon/ display to capture attention, etc.).

This chapter is organized as follows. First, we provide a review of existing empirical research on the effects of affect and belief states on performance, and a generic summary of affect assessment methods (Section 9.2), and briefly discuss specific existing work in affective assessment and adaptation (Section 9.3). Next, we describe the ABAIS adaptive methodology and the system architecture that implements this methodology (Section 9.4). We then briefly describe the task context: Air Force fighter pilot sweep task, to provide the necessary background for the concrete examples of system functionality described in subsequent sections (Section 9.5). We then outline an enhanced form of cognitive task analysis, which explicitly includes the possible effects of affect and personality traits on performance, and is therefore termed *cognitive affective personality task analysis* (CAPTA) (Section 9.6). Next we describe the process of user affective and belief state assessment and behavior prediction (Section 9.7), and the strategy selection and specific GUI adaptation strategies (Section 9.8). We then illustrate the overall ABAIS prototype functionality by a brief description of system performance in the context of the demonstration tasks: Air Force fighter pilot sweep task (Section 9.9). The paper concludes with a

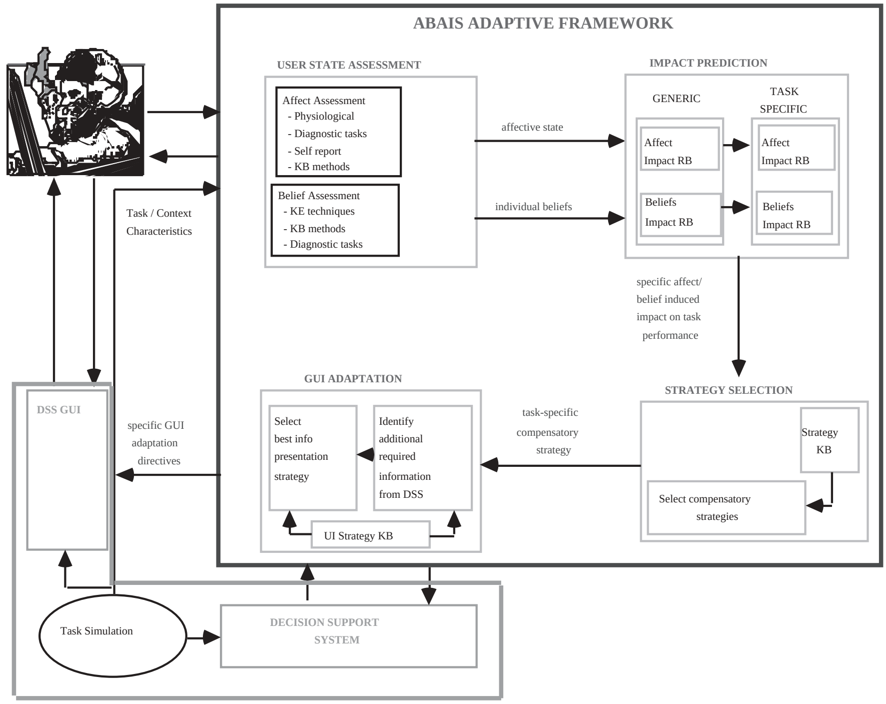

Figure 9.1: ABAIS system architecture.

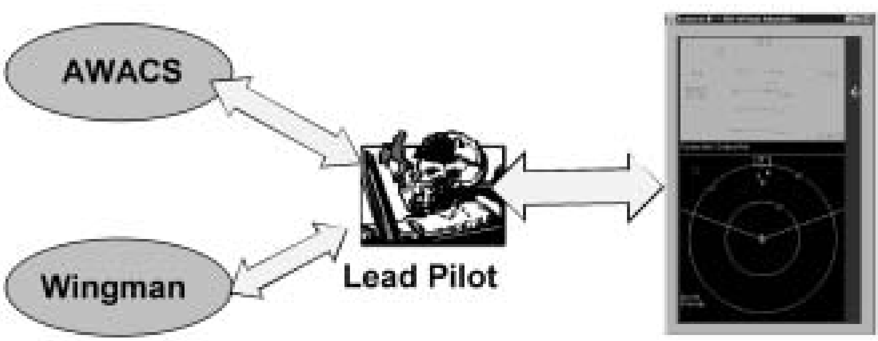

Figure 9.2: High-level diagram of key demonstration task components.

summary, conclusions, and brief outline of future work (e.g., system performance evaluation) and generalizability of the ABAIS methodology to other domains (Section 10.0).

9.2 AFFECTIVE AND BELIEF STATES: EFFECTS ON PERFORMANCE AND ASSESSMENT

This section provides background on existing research most relevant to our effort to develop an affect and belief adaptive system. Section 9.2.1 summarizes the effects of emotion on cognition and performance. Section 9.2.2 reviews generic methods for assessing affective states. Section 9.2.3 summarizes research on situation awareness and its relevance to assessing, and adapting to, the user's belief state.

9.2.1 Effects of Affective States on Performance

Although central to human development and functioning, emotions have, until recently, had a somewhat marginal status in cognitive science, neuroscience, and human factors. Over the past ten years, however, important discoveries in neuroscience and experimental psychology have contributed to an interest in the scientific study of emotion. A growing body of evidence from neuroscience research points to the existence of circuitry processing emotionally relevant stimuli (i.e., stimuli that threaten or benefit the survival of the organism or its species) (LeDoux, 1989). LeDoux and colleagues have studied fear conditioning in rats and identified a number of key results: (1) existence of dedicated circuitry processing stimuli that threaten or benefit organism or species survival; (2) evidence that emotional circuitry performs fast, less differentiated processing and behavior selection (e.g., freezing behavior in rats); and (3) evidence that this processing is mediated by connections linking sensory organs directly to emotional circuitry in the brain, specifically, the amygdala (LeDoux, 1992). Cognitive psychologists have described a variety of appraisal processes involved in inducing a particular emotional state in response to a situation (Lazarus, 1991) and several models have been proposed (Ortony et al., 1988), some of which have been implemented in computational models (Bates et al., 1992; Elliot, 1992; Scherer, 1993). Damasio and colleagues (1994) have studied humans with brain lesions and identified the role of emotion in human information processing and decision-making, suggesting that emotions "prune" the search spaces generated through cognitive processing. Recent research thus provides evidence for the impact of emotion on cognitive processing and the central role of emotion in the control of behavior. The emerging findings also begin to blur the distinction between what has traditionally been thought of as the separate realms of cognition and emotion.

Of relevance to the ABAIS system are the consistent findings by cognitive and clinical psychologists regarding the differential impact of various emotional states on cognition and a number of affective states and personality traits have been studied extensively (e.g., anxiety, positive and negative affect,

Table 9.1: Effect of Emotion and Personality Traits on Cognition: Examples of Empirical Findings

Anxiety and Attention (Williams et al., 1997; Mineka and Sutton, 1992).
Narrowing of attentional focus
Predisposing towards detection of threatening stimuli
Affective State and Memory (Bower, 1981; Blaney, 1986)
Mood-congruent memory phenomenon—positive or negative affective state induces recall of similary valenced material
Obsessiveness and Performance (Persons and Foa, 1984; Sher et al., 1989)
Delayed decision-making
Reduced ability to recall recent activities
Reduced confidence in ability to distinguish among actual and imagined actions and events
Affect Judgement and Perception (Isen, 1983; Williams et al., 1997)
Depression lowers estimates of degree of control
Anxiety predisposes towards interpretation of ambiguous stimuli as threatening

obsessiveness, extraversion, etc.). These factors influence perceptual and cognitive processes, including attention, perceptual categorization, memory, and general inferencing and judgment. Examples of findings are shown in Table 9.1. These findings provide an empirical basis for predicting the generic effects of emotional states and personality traits on performance. These generic effects can be used in the absence of task-specific information, and also serve as guiding principles for the affective/cognitive task analysis required to generate specific performance effects, in the context of particular situations.

9.2.2 Assessment of Affective States

Existing methods for affect assessment include psychological self-report instruments, physiological sensing, facial expression recognition (Ekman & Davidson, 1994; Kaiser et al., 1998; Picard, 1997), speech analysis, diagnostic tasks, and expert observer evaluation (knowledge-based assessment). However, none of these methods alone provide a definitive solution to this difficult task. Assessing affective states is an inherently difficult problem, in large part due to the variation in the expression of these states, both across and within individuals (Picard, 1997). Effective assessment of emotional states therefore requires a combined use of a number of methods. Below we provide general background information about several methods and outline their relevance for ABAIS. Section 9.3 then discusses specific affective modeling and adaptation systems using some of these methods.

9.2.2.1 Psychological Instruments/Self-Reports. Self-reports using standardized psychological instruments (i.e., “pencil and paper” or computer-administered questionnaires) represent an established means of affect and personality trait assessment, in both clinical and experimental settings. A variety of validated instruments exist for a broad range of affective states and personality traits, both “normal” and “pathological” (e.g., specific affective state and trait measures, specific personality trait instruments, social performance assessment instruments, workload and stress measures) such as the Minnesota Multiphasic Personality Inventory [MMPI] [Hathaway & McKinley, 1989]; State-Trait Anxiety Scale; Anxiety Sensitivity Index [Peterson & Reiss, 1987]; Positive and Negative Affect Scales—PANAS [Watson, Clark, & Tellegen, 1988); Beck Depression Inventory, etc.]. In addition, domain-specific instruments also exist (e.g., aviation-oriented Armstrong Laboratory Aviation Personality Survey [ALAPS] [Retzlaff et al., 1997].

While it is often the case that the best way to find what people are feeling is to ask them, this method has several associated difficulties. Specifically, (1) use of self-reports can be impractical in real-time environments except to provide background information; (2) self-reports can be inaccurate due to the user’s inability to recognize certain affective states which may, nevertheless, influence performance; and (3) self-reports may be inaccurate because the user may not wish to reveal the desired information.

In spite of these drawbacks, self-reports can be a valuable resource for affect assessment, provided the following criteria are met:

- The task environment provides opportunities for brief, simple self-assessment of specific affective states (e.g., a simple dialog box with a “Are you now feeling anxious?” and a “YES/NO” option)
- Users can be trained to accurately differentiate between the affective states of interest (e.g., high-and low-anxious state)
- Cooperation of users in providing accurate information can be ensured.

Implications for ABAIS. Existing instruments can be used in two ways as part of the self-assessment procedure in ABAIS. First, during an off-line, initial assessment, to provide background information and suggest generic effects on performance. Second, during brief on-line assessment, where one or two items would be presented to the users *during* task performance, to provide a specific, targeted assessment of their current affective state. This latter application of self-reports would need to be compatible with the task context and would not be appropriate in all situations.

9.2.2.2 Physiological Sensing. A large number of physiological assessment methods exist, varying in intrusiveness, reliability of the obtained data, and diagnosticity. Affect assessment via a combination of physiological sensing methods is currently an active research area, in part due to the technological advances in wearable computing, and in part due to the increasing interest in emotion research (Picard, 1997). While physiological sensing methods provide objective assessments in terms of measurable, physical signals, a number of issues exist regarding their usefulness in reliably identifying distinct affective states. These are both theoretical and practical. From the *theoretical perspective*, these methods rely on the assumption that different affective states have unique, detectable physiological signatures. Much research has been devoted to the identification of "basic" emotions (Ekman & Davidson, 1994) and their differentiation using physiological measures (Cacioppo et al., 1993). However, the results of these efforts are often difficult to replicate. (Note, however, recent work by Picard and colleagues [Vyzas & Picard, 1998], who report increasing success in differentiating among several of the basic emotions using physiological data.) From the *practical perspective,* physiological sensing has until recently been both cost-prohibitive and impractical, due to the amount and type of equipment necessary for accurate assessment (e.g., large, bulky equipment for heart-rate measures; uncomfortable, interfering electrodes for EEG and EMG, etc.).

Fortunately, however, there have been both theoretical and practical advances in recent years, to make selected physiological assessment feasible. *On the theoretical side*, one approach is to limit the assessment to a differentiation between high and low arousal, and positive and negative valence, rather than a large set of affective states. Arousal is reflected in a number of physiological measures, including heart rate, pupil size, and skin conductance measures. Valence is best assessed by monitoring selected facial muscles via EMG sensors (i.e., corrugator muscle activity increases during negative affect and decreases during positive affect, and activity of the zygomatic muscle increases during positive affect). *On the practical side*, the emerging technology of wearable computers makes fast, unobtrusive measurement of a variety of physiological signals feasible.

Implications for ABAIS. While a number of experimental methods are theoretically available, results of the literature search reveal that most reliably assessed affective measures are arousal and valence. The best practical signal for arousal detection is heart rate (Cacioppo et al., 1993; Hugdahl, 1995; Orr, 1998). Other measures of arousal, such as galvanic skin response, pupil size, blood volume pressure, etc., either do not provide additional data and/or are not as readily assessed. While skin conductance measures represent a better direct measure of anxiety, as opposed to arousal, the requirement of finger or palm sensors makes these impractical in computerized, automated environments.[2] The best means of assessing valence appears to be facial EMG, focusing on the corrugator and zygomatic muscle groups. The selection of specific methods and measures is thus highly task- and interface-dependent. Given the task considerations of the ABAIS prototype, the most appropriate physiological signal appears to be heart rate as a measure of anxiety level.

2. Note, however, rapidly emerging nonintrusive and wearable devices that may make complex physiological assessment practical in the near future.

9.2.2.3 Diagnostic Tasks. Diagnostic tasks represent an additional means of assessing affective state in real time, using a variety of behavioral observations and performance metrics (e.g., accuracy, reaction time, type and timing of specific errors, etc.). Diagnostic tasks require either passive user monitoring (e.g., speed of responding to alerts), or, in certain conditions, the injection of specific diagnostic probes to collect measures of interest (e.g., sequence of artificial stimuli identification tasks, etc.). A key advantage of diagnostic tasks is their ability to provide an individualized means of assessing actual performance biases in real time, rather than relying solely on indirect measures of anxiety/arousal. As with physiological sensing, while it would be unrealistic to use this method for differentiation among subtle affective states, it appears feasible to indirectly infer levels of anxiety or key personality traits (e.g., obsessiveness, aggressiveness, etc.). Thus, for example, failure of the user to repeatedly respond to critical new data can be interpreted as task neglect due to anxiety, and repeated interrogation of data sources for the same items can be interpreted as obsessiveness.

Implications for ABAIS. This approach to affect assessment appears feasible, provided the following criteria are met:

- Domain-specific diagnostic tasks can be identified and customized to individual users and task context
- Individual baseline performance data can be collected for comparison during real-time assessment
- Implementation of a nonintrusive means of collecting the necessary data in real time is feasible.

9.2.2.4 Expert Observer Evaluation—Knowledge-Based Assessment. This method uses an expert, knowledge-based system approach, where a number of knowledge bases are first constructed from knowledge elicited from experts or technical literature, or derived from cognitive task analysis. This knowledge is encoded in a variety of representational formalisms (e.g., rules, belief nets, etc.). Both static user data (e.g., individual history, personality traits, task characteristics) and dynamic user data (e.g., current affective state, workload, physiological signals, etc.) then provide data used by the inferencing mechanisms to derive likely user affective state from factors such as current task context, personality traits, and individual history. This approach in effect emulates an expert observer, familiar with the task and the user, who combines the relevant data and determines the most likely user state. A key advantage of this method is that it allows the *simulated* implementation of a combination of multiple methods by assuming the existence of a variety of static and dynamic data and integrating these during assessment (e.g., pilot's individual history, real-time task events, simulated heart-rate measures, etc.). In some sense, this approach is analogous to the cognitive appraisal theory of affect generation, which posits that affective states result from cognitive evaluations of the individual's goals and expectations, current situation, interpersonal environment, etc. A key distinction between the knowledge-based and cognitive appraisal process, other than the obvious difference between who is doing the assessment, is that the former draws on a broader variety of data (e.g., physiological data, diagnostic tasks, etc.).

Implications for ABAIS. The ability to combine a wide variety of data makes the knowledge-based approach an ideal candidate for an initial prototype implementation, designed to test the feasibility of integrating multiple assessment methods within a single inferencing formalism and architecture. In addition, there are the obvious benefits of increasing assessment reliability by integrating multiple data sources.

9.2.3 Effect of Belief States on Performance

Much recent research in decision making and skilled human performance, particularly in dynamic, real-time settings, has focused on the concept of situation assessment and situation awareness (Endsley, 1995). Briefly, situation awareness refers to the individual's ability to rapidly identify salient cues in the incoming data and map those cues onto a small set of relevant situations, which then guide further action selection. Situation assessment and situation awareness may take various forms and are highly dependent upon the mutual constraints among individuals, teamwork, and environmental factors. A series of extensive studies of situation assessment in the military and other real-time settings have been conducted by Klein and colleagues (1989) as well as others (Elliot et al., 2001; Serfaty et al., 1997; Wellens, 1993). The Klein (1997) approach has labeled this process Recognition-Primed Decision-Making (RPD), and identified RPD as a key element in tactical planning.

To the extent that affective state and personality traits influence attention, perception, and cognition, they play a major role in influencing all aspects of situation assessment and belief formation, from cue identification and extraction, to situation classification, and finally decision-selection. A critical relevant area of study is the research in cognitive biases, resulting from the application of cognitive heuristics, many of which may be unconscious (Tversky & Kahneman, 1981). Specific biases identified include confirmation bias, primacy and recency effects, over-generalization, etc.

Situation assessment, situation awareness, cognitive biases, and perceptual cues represent key elements of the cognitive-perceptual processes that help users make sense of the world. Together, these processes ultimately define the users' personal belief systems, which then guide and direct perception, decision-making, and performance. As experiences accumulate with certain degrees of regularity, a set of residual beliefs and knowledge schemas are gradually constructed which eventually result in the development of the users' *mental models.* Mental models serve as templates through which impinging sensory stimuli are organized into meaningful wholes and allow a rapid generation of expectations about the likely evolution of the world state. The use of mental models as a cognitive metaphor has been posited by a number of researchers. A common definition is that of Johnson-Laird, who defines mental models as "structural analogues of the world which may represent spatial relations between entities, causal-temporal relations among events, and contain an imaginary world model used to compute projective relations for an image" (Johnson-Laird, 1983, p. 410). He also suggests that mental models vary in form and content according to their purpose which is typically to predict, explain, or control. Mental models represent a set of mental shortcuts, which meld beliefs and schemas together for use in real-world situations.

One can thus see that beliefs are very much cognate with situation assessments (e.g., Young & McNeese, 1995) and demonstrate how "pure" cognitive processing, as advocated in human information-processing models (e.g., Lindsay & Norman, 1977), is shaped by context. In turn, contemporary approaches, for example, situated cognition (Resnick et al., 1991), distributed cognition (Woods et al. 1994), sensemaking (Weick, 1979), naturalistic decision making (Zsambok & Klein, 1997), and cognition in the wild (Hutchins, 1995) share common ground with CSE in that they suggest the mutually dependent roles among cognition, beliefs, and contextual variation. However, most all of these perspectives, including CSE, while lending credence to the value of belief formation (in some fashion), typically fail to address the role of emotions and affect.

Implications for ABAIS. The ABAIS belief assessment component primarily corresponds to the situation assessment discussed above, in that the currently active beliefs and knowledge schemas influence all stages of the situation assessment process. The assessment of a user's belief state thus amounts to the identification of his/her active mental model (sets of beliefs and knowledge schemas) that guide situation assessment. The situation assessment literature helps identify both the distinct stages of situation assessment, and the role that specific knowledge plays in this process (Klein, 1997; Lipshitz & Ben Shaul, 1997). The cognitive bias literature then helps identify the set of specific performance errors that can result from cognitive biases. Both sources provide a systematic basis for identifying possible belief states, for analyzing individual history information and applying it to dynamic belief assessment, and for identifying the relationships between specific affective states and cognitive biases.

9.3 RELATED WORK IN AFFECT AND BELIEF ASSESSMENT AND ADAPTATION

Relevant related research is conducted by the *user modeling* community. The term "user modeling," however, is used in a different sense in this community, from that typically used by the CSE researchers. Within the CSE community, this term typically implies a detailed characterization of the user's mental models in terms of some representational structure (e.g., concept maps [Zaff, McNeese, & Snyder, 1993], cognitive task-analytic structures such as goal and task hierarchies, causal models, etc.). Such models are typically nonexecutable, although in some cases may be part of an executable human performance model. In contrast, the user modeling community focuses less on the internal mental representations and more on static descriptions of behavioral and perceptual preferences (e.g., user preferences for information retrieval, alternative strategies during tutoring sessions, etc.). Nevertheless, there are important areas of overlap between the CSE and user modeling community, namely, the issues of user assessment and adaptation.

Research in this area has evolved rapidly over the past ten years and the number of systems, methods, and applications that attempt to solve these problems is too large to allow an exhaustive discussion of each potentially relevant system. The traditional nonaffective application domains include information filtering, document retrieval, web navigation (Pohl & Nick, 1999), tutoring, and personal assistants (Maes, 1994; Mitchell et al., 1994) in a variety of domains. Of particular relevance for this chapter are early concepts and prototypes for adaptive intelligent interfaces for the fighter-pilot domain (e.g, Fraser et al., 1989; McNeese, 1986). The early work in the pilot associate program is an example that focused on multi-level adaptation (Rouse, 1988). These early programs provided a much-needed experimental context for today's successful Rotorcraft Pilot's Associate and more advanced envisioned worlds (see Taylor, Chapter 8, this volume). Examples of recent user assessment and adaptation efforts include a fighter-pilot adaptive interface that assesses the pilot's workload and implements content, format, and modality adaptations in the cockpit displays (Mulgund et al., 2001) and analogous work in the context of air-traffic management (Harper et al., 2000).

The user states assessed typically consist of a variety of cognitive aspects of user knowledge, preferences, and performance (e.g., capabilities and limitations, interaction style preferences, goals and information needs, domain models, specific knowledge "bugs," generic problem-solving knowledge, etc.) (Dietrich et al., 1993). The methods for obtaining the user knowledge include implicit inferencing (e.g., probabilistic information filtering and classification approaches, knowledge-based inferencing and statistical approaches to derive user model information, machine learning techniques to automatically construct a user model from identified patterns in collected behavioral data

[McNeese, 1989; Pohl & Nick, 1999]), and explicit queries directly to the user, with varying degrees of user involvement in model construction and maintenance (Fleming & Cohen, 1999). The adaptations include modifying information retrieval criteria, changing tutoring strategies or material, and modifying user interfaces (e.g., Fijakiewicz & DeJong, 1998; McNeese & Katsuyama, 1987; McNeese, Rentsch, & Perusich, 2000).

Although the focus on affective assessment and adaptation in the broad area of user modeling is relatively recent, much interesting and relevant work exists. Systems are being developed and evaluated in applied settings, and basic research is being conducted on specific methods.

Below we provide brief descriptions of several representative systems and approaches, both those focusing on developing *tools* in particular application settings (e.g., tutoring [Elliot et al., 1997] and call monitoring [Petrushin, 2000]), and those focusing on exploratory development and assessment of particular *methods* (e.g., facial expression analysis [Kaiser et al., 1998], and physiological signal analysis [Healy & Picard, 2000]).

Elliot and colleagues have developed a pedagogical agent, based on the Affective Reasoner system (Elliot, 1992), which attempts to enhance its effectiveness through the assessment of the user's affective state (Elliot, Lester, & Rickel, 1997). The agent uses a type of cognitive appraisal process (Lazarus, 1991) to infer the affective state, implementing an enhancement of a computational cognitive appraisal model outlined by Ortony, Clore, and Collins (1988), and considers a variety of user characteristics (e.g., goals, principles that guide behavior, preferences, etc.). The assessment focus is on emotions such as hope and fear, and on the user's goals and goal characteristics (e.g., most critical goals, expectations regarding the achievement of this goal), in an attempt to capture the user's motivation. The data used include self-reports and behavior observations, and techniques include various AI-inferencing approaches (e.g., case-based abductive reasoning based on particular behavioral manifestations, recent individual history of the user, such as the "just failed on task" or "just succeeded on task"). More recent efforts attempt to infer the user's affective state based on the agent's affective state, thus implementing a form of software empathy.

In an effort to enhance and enrich human-computer interaction in general, Breese and Ball (1998) have developed an affective adaptive architecture that assesses the user's affective state in terms of the fundamental dimensions of valence and arousal, and personality in terms of the dimensions of dominance and friendliness. The system uses dynamic Bayesian belief networks to combine a variety of observable data (e.g., speech speed, facial expressions, word choice). (This work focuses more on the inferencing processes required to derive a particular state than on the data extraction itself.) Once a state and personality trait are identified, the interaction agent generates a response whose affective and personality tone match those identified in the user.

With a similar objective in mind, Klein developed and evaluated an experimental system that assesses a user's level of frustration using behavioral observations and self-reports and that implements an adaptation strategy that emulates human activities aimed at reducing negative affect (e.g., active listening, providing opportunity to vent, etc.) (Klein, 1999; Klein et al., 1999).

A number of recent efforts have attempted to assess user affective state via physiological sensing and a variety of prototype systems have been developed, primarily at the MIT Media Laboratory (http://www-white.media.mit.edu/vismod/demos/affect/AC_research/recognizing.html). These approaches assume distinct sets of physiological correlates characterizing particular states, and use a variety of sensors and wearable computer devices for data collection, coupled with complex pattern-recognition algorithms to identify unique patterns characterizing a particular state. Examples of these projects include Healy's work in assessing the user's level of stress (Healy & Picard, 2000), which uses four physiological signals (EKG, EMG, respiration sensor, and GSR), and the BlueEyes project at IBM (http://www.almaden.ibm.com/cs/blueeyes/) developing touch-sensitive input devices (e.g., Emotion mouse [http://www.almaden.ibm.com/cs/blueeyes/mouse.html]], by sensing and analyzing the user's pulse, temperature, and galvanic skin response to determine user's anxiety, stress and happiness, and using this information to determine success of computer-generated behaviors in a variety of intelligent "appliance" systems (e.g., intelligent TV-channel selector, etc.).

The BlueEyes project also includes methods using visual data based on observable behaviors, for example, facial expression (focusing on eyebrows and corners of mouth), gaze tracking, and gesture observation to assess the user's cognitive, affective, and physical states relevant to human-machine interaction (e.g., anxiety, happiness, dissatisfaction, etc.).

Extensive work in affective state assessment has been done by the Geneva Emotion Group (http://www.unige.ch/fapse/emotion/), as part of an extensive emotion research program. Particularly relevant to affect assessment is the extensive in-depth work of Kaiser, Wehrle, and colleagues, focusing on facial expression analysis (Kaiser, Wehrle, & Schmidt, 1998).

Speech is another effective source of data for affect assessment, using a variety of speech attributes (e.g., pitch, vocal energy, rate, and pauses, etc.) to differentiate among five affective states (neutral, happy, sad, angry, and fearful), and using several mathematical modeling approaches to derive the final affective state. These include K-nearest neighbors and a variety of back-propagation neural network approaches. These methods have been applied to analyze telephone conversations in support call centers and both prioritize messages and assign an appropriate human to handle particular calls (Petrushin, 2000).

In terms of pilot-vehicle adaptive interfaces, several systems attempt to assess the pilot stress level, more or less directly. The work of Mulgund and colleagues mentioned above (Mulgund et al., 2001) uses workload, which can be used as an indirect measure of stress, and performs cockpit display adaptations in response to high workload values.

9.4 ABAIS ADAPTIVE METHODOLOGY AND SYSTEM ARCHITECTURE

This section provides an overview of the ABAIS architecture and its constituent modules. Detailed descriptions of the key components—assessment and adaptation–are provided in Sections 9.7 and 9.8, after the necessary domain background information is provided in Sections 9.5 and 9.6.

9.4.1 ABAIS Adaptive Methodology

The ABAIS prototype implements a four-step adaptive methodology consisting of (1) sensing/inferring the individual's affective state and performance-relevant beliefs (e.g., high level of anxiety; aircraft is under attack), (2) identifying their potential impact on performance (e.g., focus on threatening stimuli, biasing perception towards identification of ambiguous stimuli as threats), (3) selecting a compensatory strategy (e.g., redirecting focus to other salient cues, presentation of additional information to reduce ambiguity), and (4) implementing this strategy in terms of specific UI adaptations (e.g., highlighting relevant cues or displays), that is, presenting additional information, or presenting existing information in a format that facilitates recognition and assimilation, thereby enhancing situation awareness (Endsley, 1995).

9.4.2 ABAIS System Architecture

The ABAIS system architecture (see Figure 9.1) implements the adaptive methodology described above and consists of four modules, each module implementing the corresponding step of the adaptive methodology:

- *User State Assessment*, which identifies the user's affective state and task-relevant beliefs
- *Impact Prediction*, which identifies the effect of user state on performance
- *Strategy Selection*, which selects a compensatory strategy, and
- *GUI /DSS Adaptation*, which modifies the user interface content and format to enhance detection, recognition, and assimilation of incoming data, that is, to enhance situation awareness.

Each of the modules is briefly described below, focusing on its input-output behavior. A more detailed description of the assessment and impact prediction modules is provided in Section 9.7, and of the strategy selection and adaptation modules in Section 9.8.

The *User State Assessment Module* receives a variety of data about the user and the task context, and from these data identifies the user's predominant affective state (e.g., high level of anxiety) and situation-relevant beliefs (e.g., interpretation of ambiguous radar return as threat). This key component of the ABAIS system is discussed in detail in Section 9.7.

The *Impact Prediction Module* receives as input the identified affective states and associated task-relevant beliefs and determines their most likely influence on task performance. The goal of the impact prediction module is to predict the influence of a particular affective state (e.g., high anxiety) or belief state (e.g., "aircraft under attack," "hostile aircraft approaching," etc.) on task performance. Impact prediction process uses Rule-Based Reasoning (RBR) and takes place in two stages. First, the *generic effects* of the identified affective state are identified, using a knowledge-base that encodes empirical evidence about the influence of specific affective states on cognition and performance. Next, these generic effects are instantiated in the context of the current task to identify *task-specific effects,* in terms of relevant domain entities and procedures (e.g., task prioritization, threat assessment). The knowledge encoded in these rules is derived from a detailed affective/cognitive task analysis, which predicts the effects of different affective states on performance in the current task context. The separation of the generic and specific knowledge enhances modularity and simplifies knowledge-based adjustments.

The *Strategy Selection Module* receives as input the predicted specific effects of the affective and belief states, and selects a compensatory strategy to counteract resulting performance biases. Strategy selection is accomplished by rule-based reasoning, where the rules map specific performance biases identified by the impact prediction module (e.g., task neglect, threat-estimation bias, failure-estimation bias, etc.) onto the associated compensatory strategies (e.g., present reminders of neglected tasks, present broader evidence to counteract threat-estimation bias, present contrary evidence to counteract failure-driven confirmation bias, etc.). As was the case with impact prediction, the strategy selection module relies on a detailed analysis of the task context that identifies specific strategies available to counteract the possible biases. This analysis then allows the construction of the strategy selection knowledge bases.

The *GUI Adaptation Module* performs the final step of the adaptive methodology, by implementing the selected compensatory strategy in terms of specific GUI modifications. A rule-based approach is used to encode the knowledge required to map the specific compensatory strategies onto the necessary GUI/DSS (decision support system) adaptations. The specific GUI modifications take into consideration information about the individual pilot preferences for information presentation, encoded in customized user preference profiles; for example, highlighting preferences might include blinking vs. color change vs. size change of the relevant display or icon.

9.4.2.1 Ancillary Modules. Several additional modules exist in the ABAIS prototype, enabling the simulation of the demonstration task, output of the simulation results on a simulated cockpit GUI (both adapted and nonadapted versions), and a series of displays and windows supporting the analyst-system interaction (e.g., entering user and task data, and monitoring system performance). These are briefly described below.

ABAIS Simulation Module. The core ABAIS framework is integrated within a dynamic flight simulation environment and supports two modes of system operation: (1) pilot-as-user mode, where the user actually flies the aircraft and interacts with a simulated environment consisting of other friendly aircraft, enemy aircraft, radars, and weapons; and (2) analyst-as-user, where the analyst watches a simulation of a scripted task and monitors the (scripted) pilot's performance, and the system run-time performance (i.e., results of the rule-based inferencing). Both modes include a pilot GUI consisting of key cockpit displays (see Figure 9.5).

Pilot's GUI. The pilot's GUI (see Figure 9.3) consists of four displays, corresponding to the Heads-Up-Display (HUD), which combines a variety of navigation and sensor information within a single display (i.e., heading, airspeed, altitude, MACH speed, etc.) (upper portion of the display), a window showing current incoming communication as text strings (middle window), an alert notification window (middle window), and the radar and sensor display (bottom portion of display), which combines information from a variety of aircraft instruments (e.g., active radar, IFF, NCTR, and RWR), as well as datalink from other friendly aircraft. The radar and sensor display symbology follows existing cockpit standards.

Analyst's GUI. The analyst's GUI serves three functions:

- It allows specification of all ABAIS system run-time parameters, including task script editing and selection, adaptation thresholds, and execution monitoring windows.
- It allows specification of all necessary background pilot information.
- It allows display and monitoring of ABAIS simulation and run-time data.

Prior to a run, the analyst specifies the necessary background information about the pilot. In the initial ABAIS prototype demonstration, these values were entered by the analyst. In a full-scope system, some of these parameters would be entered by the user (pilot) (e.g., self-reports and individual history information), gathered during training tasks (e.g., baseline physiological or

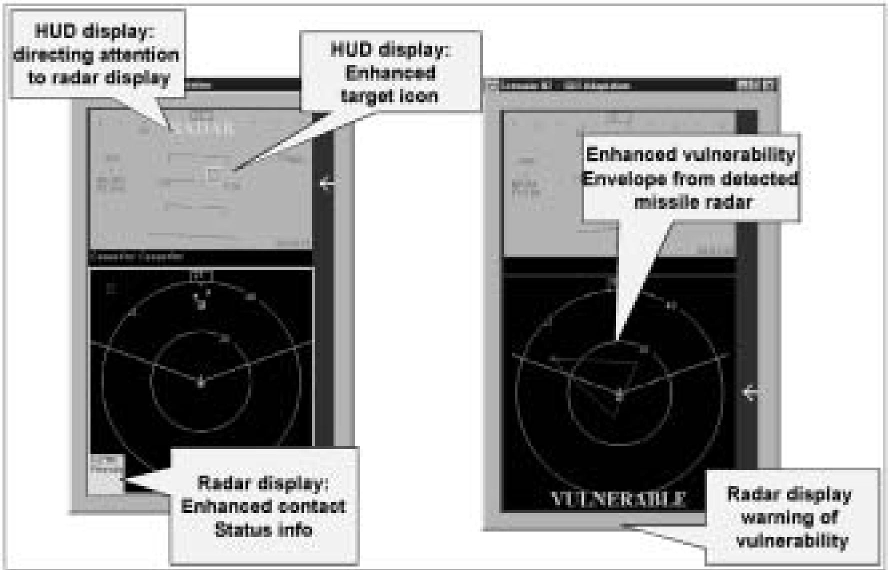

Figure 9.3: Summary of GUI/DSS adaptation strategies.

diagnostic task data), or collected automatically during an actual system run (e.g., actual physiological signals or diagnostic task results). Different categories of information are specified, including personality, skill, individual history, and adaptation preferences.

9.5 ABAIS DEMONSTRATION TASK: FIGHTER PILOT "SWEEP" TASK

Below we describe the essential details of the ABAIS demonstration task to provide the necessary background for understanding the details of the ABAIS rulebases and inferencing described in Sections 9.7 and 9.8. While the initial prototype was implemented in the context of a fighter pilot task, the overall ABAIS methodolog, and implemented framework provide a generic approach to affective adaptation and modeling (see discussion in Section 9.10.3).

9.5.1 Task Context

The demonstration task simulates a U.S. Air Force fighter pilot sweep mission, where a group of friendly pilots attempt to clear the airspace of any enemy aircraft. The aircraft is assumed to be an F–15-like fighter aircraft cockpit. During the specific mission, two friendly aircraft ("lead" and "wingman") are conducting a sweep mission over enemy territor. They are assisted by an

AWACS aircraft providing additional information, and command and control. Several unknown, presumably hostile aircraft, are approaching the friendly aircraft and the corresponding data (radar returns) are beginning to appear on the aircraft cockpit radar displays.

9.5.2 Human Context

The demonstration task focus is on the lead pilot as the "user." The lead pilot communicates with the wingman and with the AWACS aircraft operator, both via voice and electronic datalinks, which display data directly on the lead's cockpit instruments (e.g., radar display, HUD).

The lead pilot's background information (user profile) is entered by the analyst, prior to a run, by entering the user-specific data (e.g., personality traits, skill, individual history, physiological responsiveness, adaptation preferences).

9.5.3 Summary of Demonstration Task Events

Two pilots (lead & wingman) are conducting a sweep mission over enemy territory (refer to Figure 9.2). Pilots are expecting strong enemy opposition. Friendly aircraft are likely to be in the area, making fratricide a possibility. A high-anxious lead pilot misinterprets incoming unknown contact as hostile and prepares to fire by "centering the dot" on his HUD display (upper portion of the cockpit GUI display). Table 9.2 summarizes the possible effects of affective and belief states on the lead pilot's performance. At the last minute, the wingman radios that a friendly identification has been obtained on this contact. In other words, the approaching aircraft is in fact a friendly coalition aircraft. However, the lead pilot is busy targeting this aircraft and misses this transmission. Without adaptation, the lead would fire a missile and hit a friendly aircraft. With adaptation, the incoming data (friendly ID) are enhanced and the pilot's attention is directed to this information in an attempt to prevent the fratricide.

9.6 COGNITIVE, AFFECTIVE, PERSONALITY TASK ANALYSIS (CAPTA)

Given the fact that a general model of human information processing is beyond the state of the art, any user modeling effort must focus itself on particular aspects of performance during a specific task of interest or an underlying mechanism of interest. A systematic cognitive task analysis process is the foundation for the development of any such cognitive model. Since the focus

Table 9.2: Summary of Possible Affective and Belief State Influences on Pilot Behavior

Anxiety-Induced Narrowing of Attention
Lead focusing on "centering the dot"
Misses "friendly ID" voice communication from wingman
Misses results of NCTR (friendly ID) on radar display
Anxiety-Induced Perceptual Bias
Lead misinterprets ambiguous radar returns as threats
Obsessiveness-Induced Checking Behavior
Lead engages in obsessive checking behavior, delaying firing at enemy

of this effort is the influence of affect and belief states on performance, the cognitive task analysis focused not only on the space of nominal behaviors and cognitive performance, but also the larger space of possible behavior variations due to the effects of these additional factors. We term this enhanced cognitive task analysis process *Cognitive Affective Personality Task Analysis*, or CAPTA for short. CAPTA formed the basis for developing the ABAIS system knowledge bases and adaptation strategies. In this section we briefly outline the CAPTA process and distinguish it from existing cognitive task analysis techniques (9.6.1), and indicate how it supports the ABAIS adaptive methodology and relates to the ABAIS architecture (9.6.2). A full description can be found in Hudlicka (2000a).

9.6.1 Description of the CAPTA Process

The objective of Cognitive Task Analysis (CTA) is to define the user's activities during a task at a sufficient level of detail to allow computational modeling, knowledge-base definition, user-interface requirements specification, or work analysis to support the variety of tasks that comprise the definition, implementation, operation, and applications of user models.

A number of CTA techniques exist (Cooke, 1995; Essens, McCann, Cannon-Bowers, & Dorfel, 1995) using a variety of methods and representational formalisms (e.g., rules, concept maps, frames, and schemas, etc.). Their unifying objective is to define critical domain and user entities, their states, and their behaviors, including the user's actions.

CAPTA differs from the traditional CTA techniques by explicitly focusing on behavior variations due to the user's affective and belief states. This supports affect and belief adaptation by (1) making explicit the number and type of affective and belief states, and user behaviors associated with each; and (2) producing a more complete and comprehensive description of the user's possible states and behaviors. Specifically, CAPTA addresses the following:

- What is the possible set of user's affective and belief states?
- What are the likely triggers of particular affective and belief states?
- What are the likely cognitive/perceptual schemata (beliefs), and goals, expectations, and behaviors associated with each affective state?
- What are the most likely goals, expectations, and behaviors associated with each belief state?

For the purposes of the initial ABAIS architecture prototype development, we focused the CAPTA process on the identification of affective and belief states, their triggers, and likely behaviors associated with each. Table 9.3 illustrates how these categories of information relate to the ABAIS architecture.

The CAPTA application in the current context assumes a naturalistic model of decision making (Klein, 1997) where the primary skilled processing takes place at the perceptual-situation assessment stage. Once the incoming cues are assembled into meaningful schemata and categorized into situations, there is a simpler mapping process between the situation and the selected action. This theoretical model underlies the task analysis approach implemented by CAPTA. The complete CAPTA process consists of the following steps:

- Constrain the possible user behaviors (i.e., decisions); goals, expectations, and situations (i.e., high-level cognitive and perceptual schemata); and stimuli (i.e., incoming sensory cues), within the context of the scenario and task domain. Focus on both task and self-related goals, expectations, situations, and behaviors
- Define the mappings between the cues and the situations, and between the situations and the decisions
- Identify the user's dominant personality traits and their most likely effects on affective state triggering, belief formation, and behavior
- Define the user's set of possible affective-states and the most likely transitions among these states, including specific triggers
- Identify most likely sets of beliefs, goals, expectations, and behaviors associated with each affective state
- Determine how goals, expectations, and affective states influence situation assessment and decision selection.

The last four steps, along with the focus on self-related processing (i.e., goals, expectations, situations, etc.), distinguish CAPTA from more traditional CTA techniques. During these steps, the cognitive systems engineer works closely with both the users and the subject-matter experts (SME), and draws on the available empirical evidence about the effects of particular affect and

Table 9.3: Relationship of CAPTA to ABAIS Architecture Components

CAPTA Information Category	Relevance for ABAIS Architecture	Pilot Domain Example
• Possible set of user's affective states • Possible set of user's belief states	• Basis for defining specific affective/belief state assessment strategies • Basis for predicting behavioral effects of specific states • Basis for identifying compensatory strategies associated with each state	• Pilot A can be calm or anxious • Pilot B can be calm or aggressive • Pilot can believe s/he is out of danger, about to be attacked, under attack • If a particular affective state (e.g., anxiety) reduces attentional capacity, modify display to reduce attentional demands
• Likely triggers of particular affective and belief states	• Defines knowledge-base within "User Assessment" module, supporting the assessment of user's affective and belief state	• Pilot becomes anxious when large number of unknown radar contacts appear on the screen Pilot assumes any unknown radar contacts are hostile
• User's likely response to a particular situation • User's likely behavior as a function of affective or belief state	• Defines knowledge-base within "Impact Prediction" module, supporting the prediction of specific effects of user affective and belief states • Helps define knowledge-base within "GUI Adaptation" module and specific GUI adaptation strategies	• Pilot tends to delay weapon engagement • Pilot engages in excessive information gathering • Pilot detects alarms more rapidly when presented in auditory mode

belief states on perception, goal and expectation formation, decision selection, and behavior. Thus, the generic effects of the possible affective states identified from the empirical literature are instantiated within the specific task context. By combining the available empirical evidence with the practical knowledge of the domain expert, the cognitive systems engineer constructs a space of possible behaviors which takes into account not just the nominal path through the problem-solving space, but also the variations resulting from different affective and belief states. For example, the empirical knowledge that anxiety biases attention and perception towards the detection of threatening stimuli, and the interpretation of ambiguous stimuli and situations as threatening, is combined with the expert's knowledge of the task at hand (e.g., air combat), to derive the alternative possible behaviors due to a heightened state of anxiety (e.g., a pilot may interpret ambiguous radar returns as threats and fire prematurely at friendly or neutral aircraft which happens to be in the area).

9.6.2 Use of CAPTA to Support the ABAIS Architecture Development

CAPTA thus produces a comprehensive description of the possible behaviors and behavior variations associated with particular user affective states, personality traits, and beliefs, thereby generating a more complete specification of the user-task problem space. Such problem space definition then becomes the basis for defining critical knowledge-bases of the ABAIS architecture modules (refer to Table 9.5). For the purposes of ABAIS prototype development, only a subset of the complete CAPTA process was used: definition of user behaviors, task situations, and incoming cues; definition of situation-action and cues-situation mappings; influences of affect and belief states on situation assessment and behavior; and definition of user's affective state transition diagrams.

Below is a brief illustration of how these steps of CAPTA process supported the definition of the ABAIS architecture components, that is, the knowledge bases contained in the distinct modules (e.g., Impact Prediction).

9.6.2.1 Defining User Behaviors, Situations, and Incoming Cues. The CAPTA process must be grounded in a fixed set of possible actions, possible situations triggering those actions, and possible cues leading to the derivation of the situations. The first step in the CAPTA process is therefore to define the limiting conditions—that is, the possible outputs (behaviors), key intermediate states leading to these actions (perceived situations), and incoming data or stimuli leading to the perception of the situations (cues). While the end-points of this process are fixed by the situation context and user capabilities (available displays and sensory channels on the input side, and possible behavioral outputs on the output side), the definition of the situation set is an art rather than a science. This process relies on the knowledge and cooperation of the subject-matter expert, who must work closely with the cognitive systems engineer/model developer to select the most appropriate situations, at the correct level of abstraction, that provide coverage of the current task. Table 9.4 shows examples of cues, situations, and decisions in the current ABAIS fighter-pilot task context.

9.6.2.2 Defining Situation-Action and Cues-Situation Mappings. Once the sets of possible behaviors, situations, and cues are defined, the CAPTA defines the mappings between the cues and the situations, and the situations and the actions. In other words, based on task knowledge elicited from the SME, the model developer specifies which cues trigger which situations, and which situations in turn trigger which behaviors. This knowledge then forms the basis for defining the rules in the ABAIS Impact Prediction Module knowledge-base.

To identify the *situation-action mappings*, we began with the possible sets of behaviors and identified the situations that triggered each behavior. For example, a pilot will fire if he/she sees a hostile target within range and is cleared to fire. By working backward from the possible behaviors, we thus identified a series of triggering situations for each behavior. These situation-actions mappings were then expanded to cover the different user profiles, and catego-

Table 9.4: Examples of Pilot Cues, Situations, and Decisions

CUES (Incoming Stimuli)	Situations (Beliefs)	Decision (Behaviors)
Datalink—friendly | unknown | hostile	Hostile aircraft closing | closing	Fire weapon
IF—friendly | unknown	Presumed hostile aircraft opening | closing	Initiate intercept
NCTR—<aircraft type>	Unknown aircraft opening | closing	Initiate evasive action
RWR—no radar contact | hostile radar contact | friendly radar contact | SAM radar contact | unknown radar contact	Cleared to fire w/positive EID	Communicate w/wingman
Active radar—friendly | unknown | hostile	Firing range for <weapon> maximun | beyond maximum	Communicate w/wingman
Targets—closing | opening	Attacking hostile aircraft	Communicate w/AWACS
	Under attack from hostile aircraft	Focus on particular instrument {HUD |

Table 9.5: Example Rules Predicting Impact of Anxiety on Performance

Anxiety-Induced Narrowing of Attention
IF (multiple targets on radar) THEN (focused on signals representing unknowns or threats)
IF (multiple unknown/threats targets on radar) THEN (focused on nearest/fastest-approaching targets)
IF (data arriving on multiple cockpit instrument) THEN (attention focused on radar or HUD)
IF (data arriving on HUD and radar) THEN (attention focused on HUD)

Anxiety-Induced Misinterpretation of Cues
IF (unknown or ambiguous targets on radar | NCTR exist) THEN (assume targets are hostile)
IF (unknown air-to-air radar lock on RWR) THEN (assume under attack)
IF (no reply from IFF) THEN (assume targets are hostile)

rized into specific groups according to the affect and belief factors. Once the complete analysis was performed, the situation-action mappings were translated into the rule set in the ABAIS affect and belief impact prediction module.

To identify the *cues-situation mappings*, we began with the set of possible situations and identified the incoming cues that would indicate each situation (i.e., belief). For example, a hostile aircraft is closing if a radar-return exists representing a hostile aircraft and the radar-return indicates an approaching aircraft over time. Given the fact that CAPTA defines not only correct decision-making but a variety of possible distortions (e.g., misinterpretation of cues; incorrect weighting of individual cues, etc.), as well as a number of variations, this process involved the construction of extensive cues-situations mappings allowing for such distortions and variations. For example, while the presence of an unknown contact on the radar means just that and does not necessarily imply that the pilot is under attack, it is certainly a possibility that this contact may represent a hostile aircraft. In the case of an anxious or aggressive pilot, it may be a likely possibility. Thus the construction of these mappings involved the consideration of a large number of possible cues-situation mappings that might be used by various pilot types to conduct situation assessment and arrive at the consequent beliefs. These cues-situations mappings are the primary source for deriving the belief assessment rules within the ABAIS User Assessment module.

9.6.2.3 Influences of Affect and Belief States. Once these basic sets of mappings were defined, they were expanded to account for the influences of the pilot's affective and belief states. This process combined existing empirical evidence, knowledge of individual user behaviors, and task-specific expertise. A systematic analysis of the possible pilot behavior and decision-making during the course of the demonstration scenario yielded a set of possible perceptual and cognitive distortions, biases, and general variations resulting from the affect and belief states. The paragraph below describes the application of this process to the analysis of the effects of anxiety on behavior and provides examples of specific rules that result from this process.

The *generic effects of anxiety* on attention include narrowing of attentional focus, difficulty focusing attention (i.e., inability to select an action and consequent delayed reaction time), and increased attention to threatening stimuli. This narrowing of attention may also result in task neglect for other critical tasks, and a failure to detect other relevant cues.

Given this generic knowledge, the CAPTA process is then used to predict *task specific* situations where these biases may influence performance, in other words, to identify situations where ambiguous cues exist which can be misinterpreted as threatening, and to identify task segments where parallel signals may occur (e.g., two signals on radar from two different sources, radar and engine instruments, etc.) and identify points where parallel tasks take place. These then allow predictions as to which of these tasks is likely to be neglected during a state of increased anxiety (e.g., pilot is more likely to pay attention to radar signals than engine instruments or radio). Examples of *specific effects* of the generic anxiety-induced biases include:

- Focusing on target or radar display and failing to notice incoming communication from other sources (e.g., radio voice communication from wingman, AWACS, etc.) or other cockpit instruments (e.g., warnings of aircraft system malfunctions)
- Focusing on target information on HUD and failing to notice new information on radar
- Interpreting ambiguous radar-returns as threats.

Examples of specific rules constructed from this knowledge and used in the Impact Prediction module are shown in Table 9.5.

9.6.2.4 Defining User's Set of Affective States and Transitions Among Them. A key aspect of the CAPTA process is the definition of the possible user affective states. This is based on the assumption that the user's affective states represent key determinants of behavior, via their influence on both the nature of perceptual, cognitive, and motor processing, and the choice of goals, formation of expectations, and ultimately formation of situation assessment and selection of specific decisions and associated behaviors (Isen, 1993; LeDoux, 1992; Williams et al., 1997).

To implement this step of the CAPTA process we have used a process we term cognitive-dynamic behavior analysis (Hudlicka, 2000a). This approach combines concepts from psychodynamic (depth psychology) and cognitive analysis of personality and behavior (Horowitz, 1991), and focuses on both intrapsychic and interpersonal patterns of thought, affect, and interaction (core role relationship models). The objective of the cognitive-dynamic behavior analysis is to identify an individual's predominant affective states (e.g., calm, anxious, withdrawn). The assumption underlying this approach to behavior analysis is that the primary determinants of behavior are the individual's cognitive schemas and that the predominant schemata controlling behavior is triggered in part by a particular affective state. We have expanded this concept to also include the individual's goals and expectation. This expanded concept then states that behavior is determined by:

- Currently active goals and expectations, which are activated based on the
- Previous and current situation assessments and current affective state, which trigger the activation of
- Specific cognitive schemata that guide perceptual and cognitive activities and decision-making.

Figure 9.4 illustrates an example of an affective state transition diagram resulting from cognitive-dynamic behavior analysis.

The process of affect state transition diagrams necessarily involves elements of affect and belief assessment. As such, it minimally consists of combining existing empirical evidence, knowledge of individual user behaviors, and task-specific expertise. A variety of issues arise here regarding the feasibility and validity of identifying these transition diagrams, both for specific individual users, and for user populations. Detailed discussion of these issues, as well as detailed procedures for the CAPTA process, can be found in Hudlicka (2000a).

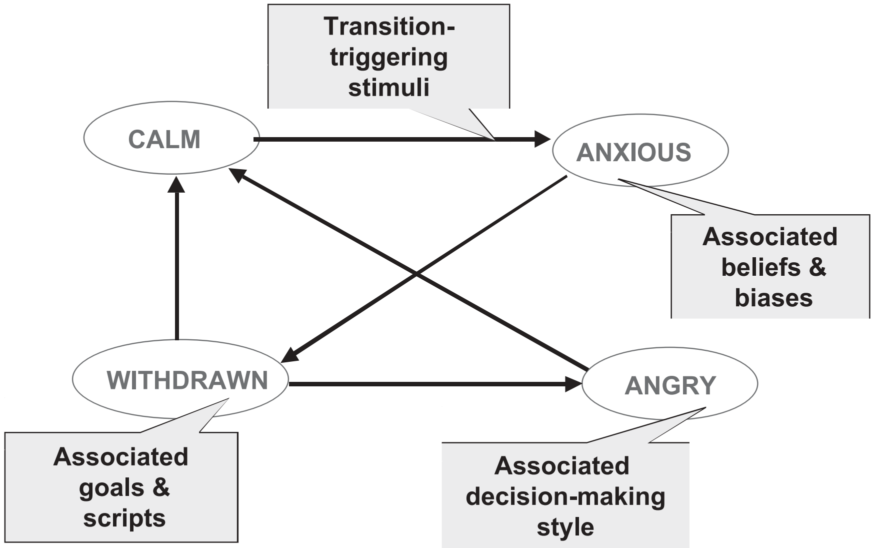

Figure 9.4: Example of an affect state transition diagram resulting from cognitive-dynamic behavior analysis.

9.7 USER STATE ASSESSMENT AND BEHAVIOR PREDICTION

Having provided the necessary background information about the ABAIS adaptive framework and architecture, and the task domain, we now turn to the key aspect of affective adaptation: the assessment of the user's affective and belief states (Section 9.7.1) and the prediction of their likely effects on performance (Section 9.7.2).

9.7.1 User Affect and Belief State Assessment

9.7.1.1 Affect Assessment. Since no single reliable method currently exists for affective assessment, the user assessment module of the ABAIS architecture provides facilities for the flexible combination of multiple methods. These include physiological assessment (e.g., heart rate); diagnostic tasks; self-reports; and use of knowledge-based methods to derive likely affective state based on factors from current task context, personality, and individual history. Each of these methods has its associated advantages and disadvantages, and none alone is currently sufficient for reliable affective state identification.

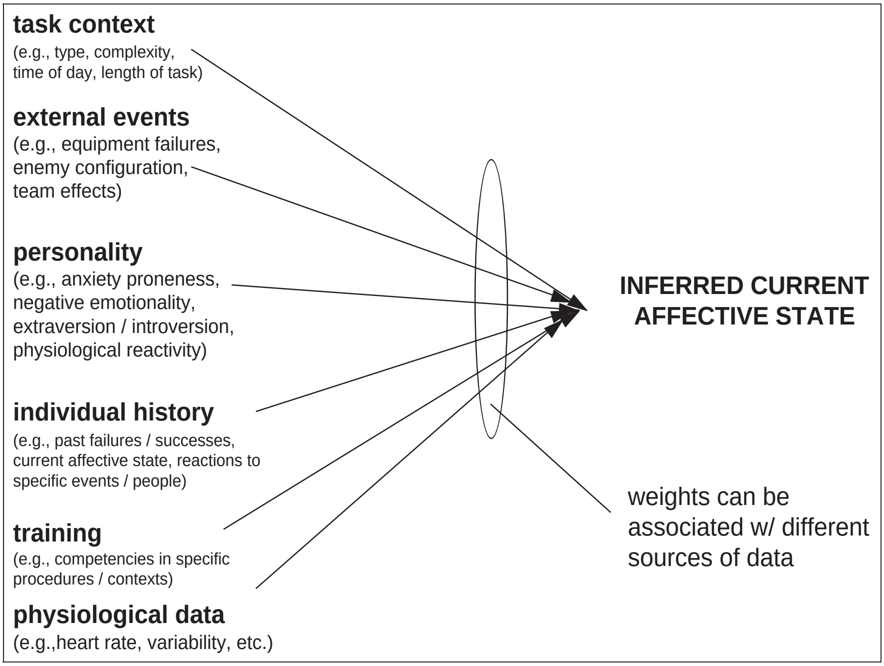

Figure 9.5: Sources of information for deriving pilot's affective state.

The initial prototype described here implements the knowledge-based approach, and assesses the user's anxiety level. The knowledge-based assessment essentially emulates the judgment of an expert observer, familiar with the key user and situation factors contributing to the user's affective state. This approach was selected for the prototype because it combines multiple sources of data (e.g., individual history, personality, task context, physiological signals), reflecting the multiple factors that influence the user's affective state (see Figure 9.5), and thus essentially provides a means of simulating the use of multiple methods. Anxiety was selected both because it is the most prevalent affect during crisis situations, and because its influence on cognition has been extensively studied and empirical data exist to support specific impact prediction and adaptation strategies.

The factors contributing to the pilot's affective state fall into two broad categories: *static* and *dynamic,* which are briefly described below. The assessment process implements a fuzzy rule-based approach which combines the influences of both static and dynamic factors to arrive at the final user affective state assessment.

Static Factors. The static factors represent influences that remain constant throughout the task (e.g., overall task difficulty, user's training and proficiency, and user's personality traits and individual history). The values of these factors are specified prior to a particular simulation via a combination of knowledge elicitation interviews with experts and users (e.g., task difficulty, level of training, personality) and off-line user assessment instruments (e.g., personality, skill level), and extensive interviews with users (e.g., individual history, personality traits). Examples of the task context and individual history static factors, and their possible values in the context of the demonstration task, are shown in Table 9.6.

Specific events from the user's history that may influence the current affective state are considered to be *individual history* factors. Given the importance of an individualized approach to affective and belief state assessment, these factors are among the most critical, particularly so since personality research indicates that the most reliable predictor of future behavior is past behavior. The individual history factors must obviously be tailored to the specific task context. Accordingly, the factors used in the initial ABAIS prototype represent the user pilot's previous experience in combat tasks.

Another critical set of static factors is the set of user's key *personality traits*, which represents a relatively stable set of characteristics that contributes to the user's affective state (e.g., emotional stability correlates with anxiety tolerance) and may influence behavior in general (e.g., obsessiveness, aggressiveness). The selection of the specific personality factors below was guided by the following criteria:

- Empirical evidence for existence of candidate factor as a distinct personality characteristic
- Empirical evidence or knowledge elicitation data indicating specific effects of the personality factor on performance, particularly in the context of the specific task (e.g., aviation and air combat tasks)
- Likelihood of the personality factor playing a role in the selected demonstration task.

Specific personality factor selection is thus informed both by domain- independent personality theory and empirical data, and, to the extent possible, by studies performed in the specific domain of interest. In the case of the ABAIS prototype, data from studies assess the pilot population in terms of a variety of standard psychological assessment instruments (e.g., NEO–PI–R, MMPI, etc. [Callister et al., 1997]), as well as instruments specialized for the fighter pilot population (e.g., ALAPS [Retzlaff et al., 1997]). Unfortunately, little systematic empirical work has been done in the general area of linking personality factors to specific performance influences and biases, at a level of analysis that would provide the type of detail necessary for real-time adaptation. We there-

Table 9.6: Examples of Static Factors Used During User State Assessment

Task Context	Individual History	Personality Traits
Task type 1 :=={offensive | defensive}	Successful situations in past :=={ egress | enemy-radar-lock—hit |	Emotional stability :=={1–10} Impulsiveness :=={1–10}
Task type 2 :=={air-to-air | air-to-grnd}	enemy-radar-lock—evasion | unknown-radar-lock—hit...}	Risk tolerance :=={1–10}
Phase :=={planning | detection | ...}	Failure situations in past :=={fratricide | repeat IFF interrogations—fratricide...}	Aggressiveness :=={1–10}
Complexity :=={1...10}	Affective reactions to individual/events :=={	Conscientiousness :=={1–10}

fore also relied on general personality research (e.g., "Big 5," "Giant 3"), and on knowledge elicited from domain experts (e.g., pilots or USAF psychologists and scientists). The objective was to capture personality traits that (1) are likely to exist in the subject population (e.g., fighter pilots), and (2) exert a pronounced influence on behavior during the performance of the demonstration task. Emotional stability was the primary factor of interest under the prototype development effort, since this factor correlates with anxiety tolerance.

Dynamic Factors. In contrast to the static, the values of the dynamic factors change during the course of the task, reflecting changes in both the external environment (e.g., incoming data from sensors such as radar contacts) as well as the changing pilot state (e.g., changes in physiological signals such as heart rate). These values are provided to the affective assessment rules throughout the course of the simulation, allowing dynamic computation of their contributions to the pilot's affective state.

An important set of dynamic factors are *external events*, which contribute to the task difficulty and, as such, influence the user's affective state. These include a variety of factors relating to the state of the environment, the equipment relevant to the performance of the task, and dynamic task characteristics (e.g., state of the aircraft, equipment failures, task-specific factors such as the geometry of the intercept, any data appearing on the radar systems, team effects).

Another set of dynamic factors are *physiological data* representing specific physiological measures collected from the user during the course of the task. Due to the high degree of individual variations in physiological signals, as well as within-individual variations over time and habituation, these measures must be normalized based on the user's baseline responsiveness measures, and baseline measures for the task and the current day. In the initial ABAIS prototype we focused on assessment of the user's anxiety level and thus considered physiological data that reflect anxiety. While a variety of measures are theoretically possible, (see discussion on physiological sensing in Section 2.2.2), the most reliable measures of state anxiety appear to be those related to arousal, that is, heart rate and skin conductance measures.[3] Although these measures reflect general arousal, rather than anxiety per se, it is assumed that during crisis situations in general, and during the demonstration scenario sweep task in particular, such arousal would be an indication of anxiety. During the initial prototype we therefore focused on heart rate as the most reliable and practical measure of arousal, using estimates derived from existing empirical literature and interviews with fighter pilots.

9.7.1.2 Belief Assessment. For the discussion below, we assume a working definition of "belief state" as representing the currently active or preferred set of knowledge constructs, schemata, or procedures guiding perception, influencing decision making, and determining the final behavioral outcome. In other words, the current belief state represents the currently active situation schemata and thus reflects the pilot's *situation assessment* and *situation awareness*. Which specific schemata are instantiated at any given time is a function of a number of factors, including user's training, individual history, personality and cognitive style differences, and affective state. Belief assessment in this context thus corresponds to what is generally referred to as situation assessment in the literature, that is, the identification of the most likely current interpretive schemata guiding situation interpretation, decision making, and subsequent action selection.

For example, in the aviation domain, a combination of pilot's training, recent events, and affective state might predispose him towards a particular interpretation of existing ambiguous data (e.g., unknown radar is hostile, approaching unknown aircraft are friendly, etc.), a pilot's training might predispose him/her toward a particular cockpit instrument-scanning pattern, and individual experience might predispose him to a specific set of expectations regarding the outcome of a particular engagement.

Given this definition of beliefs, the following problems must be addressed to identify a belief state and its potential effects on performance. *First*, the possible set of beliefs relevant for a particular task context must be identified; in other words, the situation taxonomy for the task domain must be defined. *Second*, the factors contributing to the instantiation of a particular set of beliefs during situation assessment must be identified; these can then be used to dynamically assess the pilot's belief state. *Finally,* a dynamic assessment must be performed during the task execution to determine the individual's most likely set of active schemata, that is, the dominant belief state and corresponding situation assessment. These three problems, and the corresponding solutions implemented in the ABAIS prototype, are discussed below.

Identifying the Task Situation Taxonomy. The first problem requires a detailed ontological analysis of the task domain, identifying critical cues, a taxonomy of

3. GSR may not be a practical measure in the fighter pilot setting, due to intrusive monitoring devices (i.e., finger sensors) and because the fighter pilot task environment may interfere with the data collection (i.e., finger sensors may obstruct other activities).

possible situations, and space of possible actions. This problem was addressed through the CAPTA process described in Section 9.6 above and resulted in the set of cues, situations (beliefs), and possible actions described in Table 9.6.

Factors Contributing to a Particular Belief State. A variety of factors determine the final belief state, each contributing some piece of knowledge or evidence to establish, confirm, or refute a particular belief about the current situation (e.g., unknown target is friendly or hostile). The sum total of these influences then determines the pilot's overall assessment of the current situation. There is significant overlap in the knowledge and rules used to assess the affective state and those used to infer the belief state. A critical aspect of the belief state assessment is the inclusion of the pilot's presumed affective state. This in effect allows the implicit modeling of the influence of specific affective states on cognition and distinguishes the current approach to belief/situation assessment from existing situation assessment methods (e.g., SD_PVI of Zacharias et al., 1996; Pew & Mavor, 1998).

Dynamic On-Line Belief Assessment. The process of dynamic belief assessment is the final step of user belief state assessment. During this phase the current knowledge factors contributing to the activation of particular beliefs are instantiated to derive the most likely set of activated schemata, that is the user's beliefs reflecting the current situation. This process essentially simulates, at the input-output level, the pilot's own situation assessment processes. In the context of the current demonstration scenario, the pilot's belief state is reflected in the pilot's assessment of the current situation from the available salient cues. While in theory an infinite number of situations are possible, in practice the set of situations for a particular task is generally limited (e.g., attacking versus being attacked, approaching aircraft are friendly or hostile, etc.). In fact, one of the conditions constraining the application of effective user modeling and adaptation is precisely the possibility of constraining the number of possible situations.

In the context of the ABAIS demonstration scenario we therefore limit the possible situations to those identified through initial knowledge elicitation and cognitive task analysis (see Table 9.6).

For the initial ABAIS prototype, we selected a knowledge-based approach for the dynamic belief assessment. As with affect assessment described above, this approach in effect emulates an expert observer, familiar with both the task and the specific individual. As was the case with affective state assessment discussed above, the knowledge used to dynamically derive the pilot's belief state was encoded in terms of production rules. Again, as with the affective state assessment, it is important to keep in mind that the factors, their values, and the corresponding rules, are specified in the context of the current individual-task and can be changed as that context changes. In fact, such individualized tailoring of the ABAIS knowledge-bases is the key to its successful adaptation for a particular individual, or group of individuals in a team setting. The actual belief state was then derived from a combination of static, a priori information about the pilot and the task, and from dynamic data reflecting the changing task environment and pilot state, including the pilot's affective state. The most critical categories of factors used were (1) external events (see discussion above), (2) individual history, and (3) current affective state.

External events are described above. Here we briefly outline issues associated with the use of individual history and affective state for belief assessment.

Individual history combines the training and skill factors with specific experiences that influence the pilot's situation assessment and decision-making. In other words, specific successful or unsuccessful experiences tend to predispose the pilot towards or against certain situations and maneuvers. For example, in the current demonstration scenario, occurrence of specific recent situations may bias the interpretation of current data; in other words, if the pilot has recently experienced a situation where a number of unsuccessful IFF interrogations were followed by a final identification of that aircraft as hostile, he/she may be predisposed to conclude that if an aircraft does not respond to IFF interrogations it is in fact hostile.

The pilot's affective state plays a critical role in his/her situation assessment. By taking into account the current affective state, the ABAIS user assessment module in effect implicitly models the potential biasing influences of the different affective states and provides a structure which allows the explicit representation of the positive feedback between cognition and affect that is often seen in crisis situations. In other words, increased anxiety contributes to a particular situation assessment (e.g., aircraft is being attacked by hostile aircraft), which then limits the processing of data that could give rise to alternative interpretations and further increase the anxiety level.

9.7.2 Affect and Belief State Impact Prediction

The goal of the impact prediction module is to predict the influence of a particular affective state (e.g., high anxiety) or belief state (e.g., "aircraft under attack," "hostile aircraft approaching," etc.) on task performance. Impact prediction thus represents an essential component of the overall adaptation strategy. The impact prediction process implemented in the ABAIS prototype uses rule-based reasoning and takes place in two stages. First, the *generic effects* of the identified affective state are identified, using a knowledge-base that encodes empirical evidence about the influence of specific affective states on cognition and performance. Next, these generic effects are instantiated in the context of the current task to identify *task-specific effects*, in terms of relevant domain entities and procedures (e.g., task prioritization, threat assessment). The knowledge encoded in these rules is derived from the CAPTA analysis process described in detail in Section 9.6, that predicts the effects of different affective states on performance in the current task context. This process is an essential component of building the impact prediction knowledge base, since the state-of-the-art of theoretical understanding and empirical research in personality and emotion do not allow accurate prediction of these influences in a generic, domain-independent manner. The separation of the generic and specific knowledge enhances modularity and simplifies knowledge-based adjustments.

9.8 ADAPTATION

Once the user affective and belief states are identified, and their likely impact is predicted, ABAIS identifies a compensatory strategy and selects a means of implementing this strategy (Section 9.8.1) in terms of specific user interface modifications (Section 9.8.2).

9.8.1 Strategy Selection

As was the case with impact prediction, the strategy selection module relies on a detailed CAPTA analysis to identify specific compensatory strategies to counteract the identified performance biases. This analysis serves as the basis for constructing the strategy selection knowledge bases, which map a specific behavioral bias (e.g., task neglect, threat-estimation bias, etc.) onto a particular strategy (e.g., present reminders of neglected tasks, present broader evidence to counteract threat-estimation bias, etc.).

Again, this process consists of two stages. First, generic strategy rules map the *generic* performance bias (e.g., task neglect) into a *generic* compensatory strategy (e.g., present reminders of neglected tasks). Next, the generic rules are instantiated in the task context, to determine the actual task-specific strategies. Examples of both generic and task-specific rules are shown in Table 9.7.

9.8.2 GUI Adaptation

Once the compensatory strategy has been identified, ABAIS moves on to the final step of implementing this strategy in terms of specific modifications to the user's interface. The GUI/DSS adaptation strategies are expressed in abstract terms, and are instantiated within the particular user-task context, taking into consideration the user preference profiles. In this final step of the user adaptation process, the ABAIS adaptation module performs three sequential functions:

Table 9.7: Examples of Rules for Compensatory Strategies Selection

Generic Rules	**Task Domain Specific Rules**
Anxiety	

IF (<task> importance = high) AND (pilot's assessment of <task> importance = low)
THEN
(present reminders for <task>) AND (direct attention to neglected instruments/data)
 	
IF (threat estimation bias = high)
THEN
(collect all evidence regarding radar signal identity)
 	
IF (confirmation bias = high)
THEN
(collect any contradictory evidence) AND (enhance display of evidence)
	IF (recent change in radar target status)
	THEN
	(emphasize change in status of return)
	
	IF (attention focus = HUD) AND (incoming radar data)
	THEN
	(redirect focus to radar)
	
	IF (target = unknown) AND (target belief = hostile)
	THEN
	(emphasize unknown status) AND (collect more data)

Obsessiveness	
IF (obsessiveness = high) THEN (remind of consequences of delayed decisions) (remind that no data available to provide additional information) (remind of most recent tasksd accomplished—present explicit checklists) (display task timeline and current position within timeline)	IF (likelihood of delayed attack = high) THEN (display all available info about enemy a/c) AND (display likelihood of attack by enemy a/c) AND (display envelope of vulnerability around own aircraft) AND (display reminders for attack tasks)

- Identifies additional information required based on selected compensatory strategy
- Selects best information presentation format
- Applies individual information presentation preferences and capabilities (e.g., modality preference, color blindness, etc.).

Below, we discuss some general principles guiding the selection of specific GUI adaptation method and illustrate the different alternatives in the context of the ABAIS user interface.

In general, two broad categories of adaptation are possible:

- Content-based, which *provide additional information*, and
- Format-based, which *modify the format of existing information*.

*Content-base*d *adaptation* involves the collection and display of additional data or knowledge to compensate for a particular performance bias. For example, providing additional disambiguating data about an ambiguous stimulus helps prevent an anxiety-induced bias to identify such stimuli as threats.

*Format-base*d *adaptation* involves the presentation of existing data in an alternative format, to enhance visibility, to draw attention to neglected displays, and, in general, to facilitate detection, recognition, and assimilation of data. For example, modifying some attention-capture attribute of a display such as size, color, blink rate, etc. helps draw the user's attention to the display.

These types of adaptations have been extensively evaluated in both laboratory and field settings, indicating that even small display changes can have major impact on attentional and cognitive processing (Wickens, Sandry, & Vidulich, 1983).

9.8.2.1 Level of Adaptation. Regardless of the method chosen, adaptation eventually results in a modification of specific User Interface (UI) attributes. These include changes in overall format, different choice of icons, or changes in UI elements, including color, location, size, orientation, modality, motion of stimulus, motion on periphery to redirect attention by preattentive processes. Adaptation can thus take place at any of the four levels below:

- *Icon level*. Modify individual GUI icons by modifying one of the appearance attributes (e.g., highlighting, changing its location within a display, changing color or size, etc.) or modifying the icon appearance itself
- *Display level*. Modify the display as a whole by changing the size or location of a selected display (e.g., moving a critical display to a central location of the overall UI), changing the appearance of a display (e.g., range setting on radar), or changing the contents of a display (e.g., decluttering a display)
- *Notification level.* Augment interface by inserting new, or modifying existing, alarms and alert notifications. Examples of notification level adaptations include adding a notification string regarding desired focus of attention (see for example "RADAR" on the HUD display or "VULNERABLE" string on the radar display in Figure 9.8), or adding an icon to a display to represent new information (see triangle in Figure 9.8)
- *User interface level.* Implement global changes to the user interface as a whole or insertion of display elements designed to focus attention on particular areas of the overall UI. Examples of UI level adaptations include a reconfiguration of the entire set of instruments on the UI to reflect a different system mode, increasing the redundancy of warnings (e.g., adding an auditory warning to a visual one, etc.), or the insertion of attention-capturing and attention-directing elements designed to direct the user's attention to a particular icon or display.

Each of these levels affords different alternatives and is more or less suitable for a given situation, depending on the task, task context, and the individual. A summary of the adaptations implemented within the ABAIS prototype is shown in Figure 9.3.

9.8.2.2 Individualized Adaptation. To be effective, the above strategies must be customized by taking into account the user's (e.g., the pilot's) display and modality preferences (see Table 9.8). This is critical to any adaptive approach, due to the large individual differences that exist in human information processing and decision-making. ABAIS therefore allows the specification of multiple user display preference profiles (e.g., knowing that a particular user has a high-sensitivity to auditory signals, ABAIS suggests that auditory warnings be used to capture attention).

9.9 DEMONSTRATION OF ABAIS SYSTEM PERFORMANCE

To demonstrate the ABAIS adaptive methodology and prototype performance, we defined several representative pilot profiles (high and low anxiety), varying in personality (obsessiveness, aggressiveness), training, individual history, and adaptation preferences. Their performance within scenario segments was simulated, generating varying levels of anxiety and alternative situation assessments at different points. Due to the precise timing required to demonstrate the adaptation GUI changes, the emphasis during this initial effort was on developing the analyst-as-user mode[4] and the associated script-based simulation, which allows precise control over the external task events necessary to demonstrate the real-time adaptation.

The pilot's anxiety levels were assessed, resulting in GUI/DSS adaptations. Specifically, ABAIS predicted that the heightened level of anxiety would cause narrowing of attention and interpretation bias towards threats (see box in Figures 9.7 and 9.8 for a summary of the ABAIS-derived pilot affective and belief states), possibly causing the pilot to fail to notice a recent change in status of radar contact from unknown presumed hostile to friendly. ABAIS therefore suggested a compensatory strategy aimed at preventing possible fratricide by (1) directing the pilot's attention to the display showing the recent status change and (2) enhancing the relevant signals on the radar to improve detection (see Figures 9.6 through 9.8). Specifically, the blinking, enlarged, contact icon on the HUD display indicates a change in status. The blinking "RADAR" string displayed on the HUD, the pilot's current focus, directs the pilot to look at the radar display, which shows an enhanced contact icon indicating a change in status, with details provided in the text box in lower left corner of the display.

4. This is in contrast to the alternative user-as-pilot mode where the user actually flies the simulated aircraft during the scenario.

Table 9.8: Pilot Information Preference Profile:
Categories of Information and Related GUI Modification Options

Information Category	Options
Preferred means of enhancing visibility	Color; Size; Blinking
Preferred color for alarms	Red solid; Red outline
Preferred alarm notification modality	Visual; Auditory
Preferred attention capture means	Movement at visual periphery; Shift display to foveal region; Enhance icon visibility; Display arrow pointing to desired icon; Superimpose blinking icon

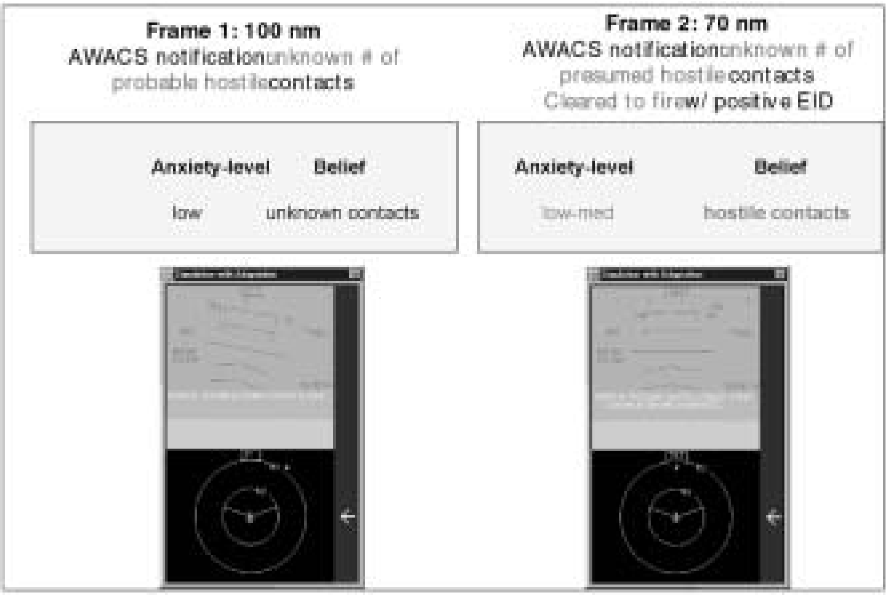

Figure 9.6: Frames 1 and 2 of the demonstration scenario: No adaptation occurs.

Informal preliminary ABAIS evaluation by an expert pilot indicated the following: (1) underscoring the importance of nondramatic, "benign adaptations," (2) general approval of the GUI adaptation strategies and modifications, (3) questions regarding the system's ability to perform *accurate* assessment in *real-time*, (4) a degree of skepticism regarding the need for affective adaptive system in an *operational*, versus training, fighter pilot cockpit, and (5) but at the same time overall enthusiasm for this type of research. A plan for extensive empirical evaluation to formally address these issues is outlined in Section 9.10.3

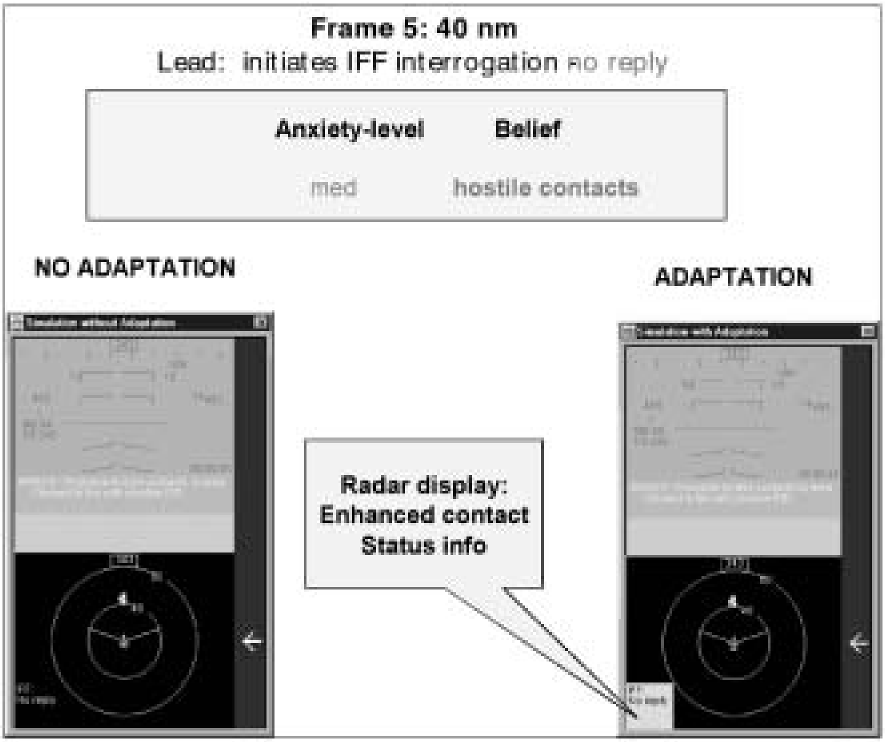

Figure 9.7: Frame 5 of the demonstration scenario: Adaptation occurs to enhance visibility and status of ambiguous radar returns.

9.10 SUMMARY, CONCLUSIONS, AND FUTURE WORK

9.10.1 Summary

The primary result of this effort was a proof-of-concept demonstration of an ABAIS, designed to provide individualized GUI and DSS adaptations based on the user's affective and belief state. ABAIS implements a four-stage adaptive methodology for the assessment of, and adaptation to, the user's affective and belief states which goes beyond traditional cognitive systems engineering practice. The ABAIS adaptive methodology was implemented within a software prototype, and demonstrated in the context of an Air Force sweep mission task. Several representative pilot profiles were defined, varying in personality, physiological responsiveness, training, individual history, and adaptation preferences. Their performance within selected scenario segments was simulated, generating varying levels of anxiety and alternatives in situation assessments at different

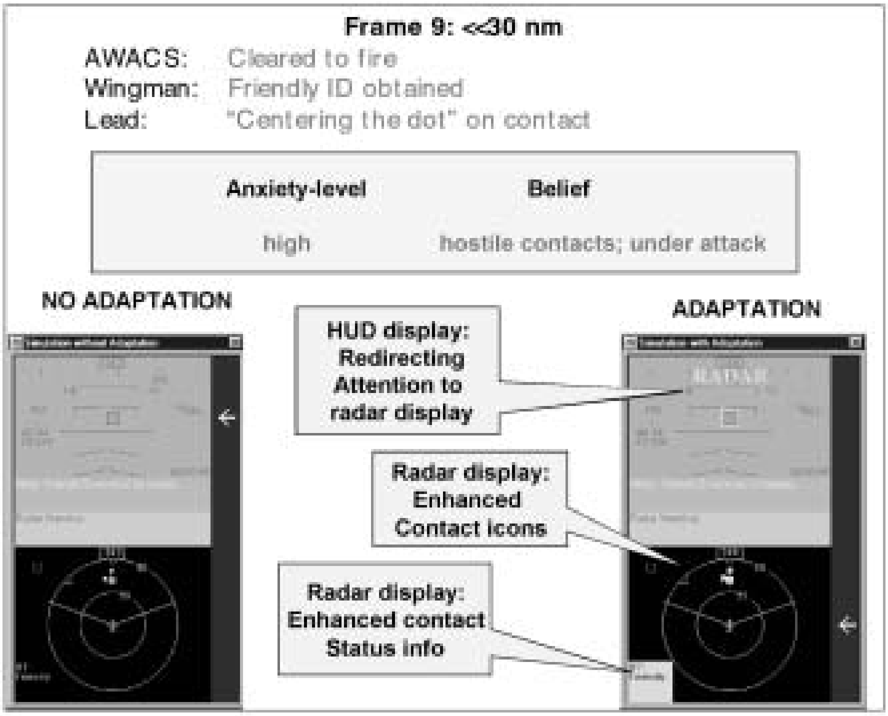

Figure 9.8: Frame 9 of the demonstration scenario: Adaptation occurs to redirect attention and enhance visibility of incoming data to prevent fratricide.

points during the scenario. The pilot's anxiety levels were assessed using the available data, resulting in GUI/DSS adaptations derived via the ABAIS adaptive methodology, using rule-bases in the four ABAIS modules. Specifically, ABAIS predicted that the heightened level of anxiety would cause narrowing of attention and interpretation bias towards threats, possibly causing the pilot to fail to notice a recent change in status of radar contact from unknown presumed hostile to friendly. ABAIS therefore suggested a compensatory strategy aimed at preventing possible fratricide by augmenting the existing cockpit GUIs to (1) direct the pilot's attention to the display showing the recent status change and (2) enhance the relevant signals on the radar to improve detection.

9.10.2 Conclusions

Development of the ABAIS proof-of-concept prototype demonstrated feasibility of the overall adaptive methodology and its implementation. ABAIS assessed the user anxiety level and belief states using a knowledge-based approach and information from a variety of sources (e.g., static task context, dynamic external events occurring during the scenario, individual history, personality, training, and simulated physiological data), predicted the effects of these states within the constrained context of the demonstration task, and suggested and implemented specific GUI adaptation strategies, taking into account the user's individual information presentation preferences (e.g., modified an icon or display to capture attention and enhance visibility). An empirical study with actual pilots flying the ABAIS simulation and providing real-time assessment data would be required to fully assess the actual effectiveness of the assessments and adaptations in an operational context (see discussion below).

Development of a remote heart-rate monitor and its linkage with the ABAIS user-interface successfully demonstrated the feasibility of nonintrusive heart-rate monitoring, providing this information to the system, and making specific changes in the user-interface as a result of detected changes. While the monitor was not integrated into the User Assessment module due to time constraints, these preliminary results indicate that such an integration is feasible.

The implementation of the ABAIS prototype demonstrated general feasibility of the adaptive methodology, and provided information about the specific requirements for a successful, operational affective adaptive interface; namely:

- Limiting the number, type, and resolution of affective states (e.g., distinguishing between high versus low anxiety)
- Using multiple, complementary methods and multiple data sources for affective state assessment
- Providing individualized user data, including details of past performance, individual history, personality traits, and physiological data
- Constraining the overall situation in terms of situation assessment and behavioral possibilities
- Providing a wide variety of task-specific data in an electronic format
- Fine-tuning the rule-bases and inferencing to "personalize" the system to the individual user-task context, and
- Implementing "benign" adaptations, that is, GUI/DSS modifications that at best enhance and at worst maintain current level of performance (e.g., adaptations should never limit access to existing information).

9.10.3 Future Work

The objective of the initial ABAIS prototype was to implement a proof-of-concept demonstration of the ABAIS adaptive methodology, implemented within an adaptive system architecture. The existing prototype indicates that this represents a feasible approach to affective adaptation. However, much work remains to be done to demonstrate its effectiveness in an operational setting, to implement additional enhancements, to validate and streamline the CAPTA process, and to generalize the ABAIS system to other domains. Several of these directions are briefly outlined below.

9.10.3.1 Evaluation. The most critical next step is an empirical study demonstrating improved human-system performance with adaptation and providing feedback about the ABAIS methodology, architecture, and knowledge-base enhancements, shortcomings, and operating constraints. Both qualitative (e.g., cognitive task walkthroughs, protocol analysis; heuristic evaluations) and quantitative (e.g., traditional empirical evaluations) are planned. Collectively, the results from these evaluation experiments will provide specific performance enhancements, shortcomings, and constraints, which, together, will define future improvements to the original ABAIS methodology, architecture design, and knowledge bases. Through successive approximations the ABAIS prototype would be revised (and reevaluated) to improve system effectiveness and human-system performance.

9.10.3.2 Generalizability. The next step is to demonstrate the generalizability of the ABAIS methodology and architecture across tasks and domains. ABAIS was designed to maximize generalizability. Specifically, the following elements apply across domains:

- ABAIS four-step adaptive methodology
- ABAIS architecture framework
- Assessment model integrating multiple factors
- Rules capturing generic effects of affective-state biases and generic compensatory strategies
- Integration of generic empirical data with task-specific domain data to identify possible effects of affective and belief states and possible compensatory strategies, and
- User-interface modification framework (format/content and levels of adaptation).

In addition, the CAPTA task-analytic process underlying the development of the ABAIS architecture knowledge-bases is also domain independent.

However, to implement ABAIS in a different task domain, a number of system modifications must be implemented by the developer and cognitive systems engineer, to identify the task and domain specific data and background information about users, and enter these into the existing ABAIS framework and architecture. Specifically, the following steps would be required:

- Detailed CAPTA to identify domain and task-specific effects of particular affective and belief states
- Detailed CAPTA to identify domain and task-specific compensatory strategies for their effects
- Construction of domain-specific components of the "Impact Prediction" and "Strategy Selection" KBs
- Entering user background data (individual history, personality traits, training, etc.)
- Development of an appropriate task simulation module, and
- Development of task-and domain-specific user-interfaces.

Again, an empirical evaluation will be required to determine the exact level of effort required to perform such a translation, to quantify the benefits offered by the ABAIS architecture components, and to identify any constraints to such domain transitions (e.g., applicability of generic knowledge across domains, etc.).

9.10.3.3 Enhancement and Integration of Multiple Assessment Methods. The ABAIS architecture was designed to accommodate multiple methods of affect and belief assessment, with the initial prototype focusing on the knowledge-based approach. Future work in this area therefore includes the implementation and exploration of the integrated use of multiple, complementary methods; enhancing the types of data processed by these methods (e.g., user's goals, specific knowledge types); enhancing the inferencing algorithms used during the assessment process; enlarging the set of affective and belief states identified; and addressing a variety of issues such as contradictory data and assessment resolution. Such integration will then allow the exploration and evaluation of the best "mix" of these methods for particular task types, domain types, or task-domain-user combinations. We would also like to explore a variety of second-order effects to enhance the reliability of affect assessment (i.e., explicit representation and analysis of the interaction among distinct affective states and among multiple factors influencing a particular affective state).

The field of affective computing is in its infancy. The confluence of technologies that facilitate affective assessment and adaptation on the one hand, and the increasing need and desire for such functionalities, provide a rich environment within which to investigate a number of fundamental issues about the role of emotion in human and human-computer performance and interaction. Key questions include issues such as to what extent are existing user modeling and adaptation methods applicable to affective adaptation? What emotions should and can be recognized, modeled, and adapted to in human-machine interfaces? When should an agent attempt to enhance the user's affective state? When should it adapt to the user's affective state? When should it attempt to counteract it? In addition to this, a number of ethical issues emerge once affect enters the stage. Canamero offers an excellent summary of some of the affect-related issues that must be addressed by the user modeling community (Canamero, 1998).

The work described here represents an attempt to integrate affective computing considerations and methods into the practice of traditional cognitive systems engineering and HCI design, in other words, to move beyond the traditional cognitive and psychophysical factors in designing the human-machine interface, by explicitly integrating affective and personality considerations into the design process via CAPTA. While the initial prototype was developed within a military aviation task context, we believe that the results are applicable to a broad variety of nonaviation and nonmilitary domains.

We conclude with a quote from a virtual agent of yore: “This fills my head with ideas, only I don’t exactly know what they are” (Carroll, 1941).

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